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Review of hybrid, plug-in hybrid, and electric vehicle market modeling Studies

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ABSTRACT

Hybrid, plug-in hybrid and electric vehicles (HEVs, PHEVs, and EVs) are emerging automotive products that have the capability to increase vehicle fuel economy, but at an incremental purchase cost relative to conventional vehicles. In general, their reduced petroleum consumption and improved efficiency provides life cycle economic benefits to consumers, society, automakers, and policymakers. These stakeholders have sought to understand the role of HEVs, PHEVs, and EVs in the future vehicle fleets by estimating the diffusion rate of these technologies into the automotive marketplace. This review presents a comprehensive summary of the literature of HEV, PHEV and EV penetration rate studies, their methods, and their recommendations. These studies have applied a suite of analytical and computational tools to model the consumer acceptability of these technologies under a wide variety of policy and macroeconomic scenarios. The results of these studies are compared and synthesized to understand the strengths and weaknesses of the field and to propose further means for improvement of advanced technology vehicle market modeling exercises. On the basis of this review, the authors recommend that modeling of HEV, PHEV and EV penetration rates should include improved interfaces with consumer surveys, modeling of automakers' actions, federal and state policy and its effect on automotive markets, competition among technologies, market volume, vehicle classifications, and model parameters sensitivity analysis.

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1. Introduction

Hybrid, plug-in hybrid and electric vehicles (HEVs, PHEVs, and EVs, e.g. P/H/EVs) are emerging automotive products that have the capability to increase vehicle performance and fuel economy, and to reduce the environmental impacts of personal transportation. HEVs were introduced in limited production in 1997. PHEVs were introduced to limited production in 2004 and to mass production in 2011 [1], and EVs were introduced for sale to the public in 2011.

Many studies have forecasted that P/H/EVs will be a growing component of the US vehicle fleet in the future. These forecasts have served the needs of society, automakers, electric utilities, and policy makers in understanding what the impact of P/H/EVs will be on their sphere of influence. Society seeks to understand the benefits that it will accrue from more efficient vehicles [2–7]. Automakers seek to understand the market potential of each vehicle technology with the goals of designing salable products and of meeting regulatory fuel economy and CO_2 emissions standards [2,8]. The Utility industry seeks to model and forecast the new electricity infrastructure demand under different transportation technology scenarios [2–7]. Policymakers seek to be able to adjust and understand the impact of present and future regulatory standards, and to understand domestic and foreign energy demand [2,4–15].

Market forecasting is a well-developed field of study with practitioners in the fields of economics, business, finance and systems engineering, but forecasting of P/H/EVs market share in the light-duty passenger vehicle fleet is complicated by factors that are difficult to model using the classical tools of market forecasting. First, PHEVs and EVs are a new automotive technology that has only just been introduced in the last years [1]. Only sales data since model year 2011 is available for validation of any PHEV and EV market model. Second, PHEVs and EVs require consumers to shift their behavior away from fueling at a gasoline station (the normal mode of fueling for conventional HEVs) toward plugging in their personal vehicle [5]. Only a few studies have attempted to quantify consumers' preference toward this change in behavior, and the fuel type change makes questionable the use of historical HEV and conventional vehicle (CV) sales data. Third, PHEV and EV fuel consumption is measured in terms of either fuel consumption (L $(100\,\mathrm{km})^{-1}$), or energy consumption (ACW-h $(\mathrm{km})^{-1}$), or both. Consumers' evaluation of PHEV and EV ownership costs will require a weighting of these energy consumptions and their costs based on consumers' driving habits, the means by which they are billed for this energy, and consumer preference. Fourth, the makeup of an automotive industry vehicle fleet is highly regulated within the US. The pricing (and therefore consumer preference) for high-fuel efficiency vehicles is presently influenced by regulation including fleet fuel economy requirements [8,10], and low carbon fuel standards [4,8,10]. Fifth, any analysis of vehicle sales in the US automotive industry is complicated by its oligopoly, by its relatively long and relatively constant product development lifecycles, by the used car market, by automaker's finance business units, and more [16].

Researchers have recently been developing market forecasting models that can include these types of complications, but the methods, scope, fidelity, and results that are the outputs of these models differ greatly among studies. The objectives of this paper are to synthesize an understanding of the state of the art in P/H/EV market forecasting, and to develop recommendations for improving the utility of these market forecasts for decision making. To these ends, this paper first presents a review of the published forecasts of HEV, PHEV and EV market share, which includes a cataloging and critique of the three main modeling methods that have been applied to automotive market forecasting. Next we present a synthesis of the results from some key P/H/EVs market forecast studies that have been performed to date. The recommendations and conclusions section provides means for improving the utility of P/H/EVs market forecasts from the point of view of automotive and utility industries.

2. Review of market forecast models for HEVs, PHEVs, and EVs

2.1. Overview

Many researchers have developed models to estimate the penetration rate of currently available HEV technologies and new PHEV and EV technologies in the US market. These models can be characterized by the modeling technique that they use to represent the interactions within the marketplace. The three major modeling techniques used in the literature on P/H/EV, market forecasting are: agent-based models, consumer choice models, and diffusion and time series models.

2.2. Agent-based models

2.2.1. Agent-based modeling overview

Agent-based modeling (ABM) is a computer based simulation method that creates a virtual environment to simulate the action and interaction of each agent. Agents are entities or individuals that have control over their interaction with other agents in the system model. Each agent is supplied with internal characteristics which dictate their interactions among other agents in the environment. ABM has been applied to many fields including population dynamics, epidemiology, biomedical applications, consumer behavior, vehicle traffic, and logistics simulation [17–28]. In the field of vehicle technology adoption, ABM has been applied by many practitioners [2,3,11,12,29,30]. These ABM vehicle technology market forecasting studies have defined different agents that operate in the modeling environment including consumers, automakers, policymakers, and fuel suppliers [2,3,11,12,29,30].

The demand for vehicles is represented by consumer agents. The consumer agents are characterized by their demographics and preferences. These characteristics have included gender, age, income, location, social network, lifestyle, daily driving needs, transportation budget, ownership period, and preferences to vehicle class, fuel type, safety, reliability, powertrain types, and performance. The consumer agents' behavior during the ABM simulation is determined by their needs and preferences when acted upon by the exogenous vehicle supply and market conditions.

The supply for vehicles is represented by automaker agents supplying vehicles from suite of vehicles characterized by vehicle class, fuel type, safety, powertrain characteristics, performance and costs. Automaker agents have access to vehicles with

improved fuel economy but vehicles with high fuel economy are modeled as requiring time to develop and may come with higher incremental cost compared to CVs. Automaker agents attempt to meet consumer demand for vehicles while maximizing profit and meeting policy and regulatory requirements [2,12].

Policymaker agents set many of the policies and standards under which automaker agents and consumer agents must act. Their actions are based on factors including, energy demand, oil security, and global environmental goals. Policymaker agents' actions will be to set new policies such as subsidies, tax rebates, sales tax exemptions or increasing gasoline taxes to motivate consumers' adoption of more fuel efficient vehicles [2,12].

Fuel supplier agents control fuel resources and acted on by consumer demand for fuel, policies including Clean Fuels Standards, and fuel resources availability. When there is an increase in fuel prices, consumers are going to shift more fuel efficient vehicles or adjust their driving habits while not exceeding their personal transportation budget [2,31].

2.2.2. Review of key agent-based P/H/EV modeling studies

In this section, we review some key studies that have used ABM to estimate the adoption rate of HEVs, PHEVs and EVs.

In one of the most complete recent ABM simulations, Sullivan et al. [2] developed an ABM considering a variety of consumer types, economic situations, and policy conditions. Four classes of agents are present in the simulation: consumers, government, fuel producers, and vehicle producers/dealers. Decision-makers interact in every cycle (1 month) where consumers choose among twelve vehicle models from three producers. In every cycle, consumers decide whether it is time to purchase a new vehicle or change their driving mileage to remain within their transportation budget limit. Vehicle dealers monitor their sales and profits, while government agents monitor fuel consumption, carbon emissions and new vehicle introductions in order to adjust current policies to meet their objectives. The model was tested under different scenarios. These scenarios included stress free market conditions, gasoline shock, vehicle pricing changes, as well as van, SUV, and HEV introductions. The results of this study showed that under the current policy case the PHEV fleet penetration rate would be insignificant, less than 1% over 10 years. Combinations of tax rebates, PHEV subsidies and sales tax exemptions could enable a significant increase in the penetration rate of the PHEV technology. Under this more active policy scenario PHEVs are estimated to reach 4–5% of sales by 2020 with more than 2% fleet penetration rate [2]. This same model was used in the PHEV Market Introduction Study by Sikes et al. [4] to study new technology penetrations in the US over different market and policy conditions. Four scenarios were examined and the results show that the projected PHEV fleet penetration would range from 2.5% to 4% for the period 2015–2020.

In another recent study, Eppstein, et al. [11] developed an ABM to estimate the adoption rate of PHEVs using only consumer agents. The consumer was assumed to consider PHEVs' environmental and financial costs and benefits based on their personal behavior and their knowledge of the technology. This study attempts to answer the question: how much is an agent willing to pay for PHEV technology and its projected economic and environmental benefits, and what policy makers and automakers about the possible set of policies and actions that effect PHEV adoption rates. Consumer's attributes considered in the study were: annual salary, age, home location, vehicle ownership time before buying another, annual distance traveled, physical neighborhood radius, social network radius, threshold for willingness to consider PHEV, social influence, personal "green-ness", fuel operating cost, economic life considered, current vehicle age and current vehicle fuel economy. Sensitivity analysis included investigation of the assumptions regarding fuel price, PHEV price, rebate availability, and the number of agents performing fuel cost estimation. This study is notable in that it includes models of many of the barriers that might affect the introduction and acceptance of PHEVs and lead to a slow penetration rate. These barriers included consumer's unfamiliarity with PHEV technology, PHEV battery life, battery replacement cost, long recharging time, future fuel prices uncertainty and short driving range. The study presented the results of the model in terms of trade-off in agent selection of HEV and PHEV 40 versus mean threshold ($T=0$–100% shifting from being an early adapters ($T \leq 0\%$), early majority to not considering PHEV ($T \geq 100\%$)). Results show that after 10 years the penetration rate of HEV approximately will have an increase between 25% and 38% where the increase will be between 30% and 60% after 20 years. After 20 years the penetration rate of PHEV approximately will decrease from 15% to 0 % at $T=0\%$ and 38–1% at $T=40\%$ [11].

Cui et al. [3] developed PHEV adoption model called a multi agent-based simulation framework to model PHEV distribution ownership at a local residential level. This study attempts to identify zones where PHEV penetration level increases quickly and then estimates the impact of PHEV penetration rate on the local electric distribution network. The model integrates the consumer choice model of Sikes et al. [4] to estimate consumers' vehicle choice probability, a consumer transportation budget model to estimate the time when a consumer will search for a new vehicle, and a neighborhood effect model to predict consumers' vehicle choice. Some of the factors found to affect PHEV penetration rate were gasoline prices, consumers' ability to calculate vehicle fuel saving, PHEV price, battery range, vehicle purchase options, social and media influence.

Other studies have developed a consumer behavior model using the ABM framework to estimate new vehicle technology market demand under the impact of greenhouse gas emission policies [12]. Garcia [12] used the individual logic model developed by Boyd and Mellman [32] to estimate consumers' vehicle choice probability. The paper describes the relationships between vehicle technology options, GHG policy and consumers' behavior [12]. A study by Zhang [33] adopts the model developed by Struben and Sterman [9,33] to estimate the adoption rate of diesel vehicles in Europe using the diesel vehicle registration historical data. The model was found to have a better fit to key patterns of the diesel vehicle registration historical data than the Bass [34] model [33]. Zhang observed that a decrease in vehicles operating costs and an increase in its performance yield an increase in diesel vehicles adoption. Stephens [31] used an ABM to estimate the electricity demand, fuel demand and the resulting greenhouse gas emissions associated with PHEVs. In their model, PHEV drivers are found to be less sensitive to fuel prices than CV drivers. Another study by Zhang et al. [35] developed an ABM that combines empirical and survey data results to investigate the effects of technology push by automaker agents, of market pull through consumer social networks, and through regulatory push through CAFE standards [35]. Shafiei et al. [36] developed an ABM to study EV's market share in Iceland's passenger car fleet over the period 2012–2030. Brown developed a mixed logistic regression model and agent-based model to simulate EV diffusion in Boston, USA [37]. He found that adoption rate is sensitive to technology prices, vehicle class, and EV range.

2.2.3. Agent-based modeling summary

ABM has been applied to many scientific and engineering fields including vehicle technology adoption. Some ABM vehicle technology adoption studies define consumers as the primary agent, whereas other studies have expanded the modeling

environment by including automakers, policymakers, and fuel suppliers as decision-making agents.

The advantages of using ABM are that it uses agents' individual characteristics, needs, limits, and preferences when simulating their behavior and interactions in the modeling environment. In general, this allows for models of consumer preference to be developed on the basis of both data-driven and hypothetical consumer behavior modeling. By modeling vehicle purchasing decisions at an individual level, ABM allows for consideration of complexities in the market such as transport mode changing, the role of social networks, and a limited personal transportation budget.

The disadvantages of ABM studies are their complexity. ABM models are generally more difficult to verify and validate, and agent-level data and elasticities can have large effects on the overall modeling results if their sensitivities are not assessed. To date, ABM studies have primarily validated the results of ABM modeling by performing sensitivity analysis to market conditions scenarios rather than sensitivity analysis to modeling methods and data.

2.3. Consumer choice models

2.3.1. Consumer choice modeling overview

Discrete choice models and logit models have been used in the literature to describe individual and collective decision making. Logit models are a commonly used means for modeling the probabilistic preference of consumers, while discrete choice models calculate the probability of a specific product being chosen among alternatives under the influence of these preferences.

Numerous studies have used these consumer choice models to model vehicle purchase and holding decisions. These studies have incorporated logit models of consumer preference to vehicle technology, class, make, and characteristics. These models are most commonly derived from combinations of purchaser demographic data and past vehicle sales data. For technologies such as PHEVs and EVs, where such data does not exist, the sensitivities of the purchasing decision to the attributes of the vehicle must be estimated or be derived from survey [38]. Some attributes estimated in consumer preference modeling of new vehicle technologies include the sensitivity to technology incremental cost, battery replacement, refueling/charging infrastructure availability, refueling/recharging time, maintenance cost and driving range [39].

The two different logit models used in the automotive consumer preference literature are the multinomial logit model (MNL), which represents the probability of choosing an alternative over all alternatives [32,40–47], and the nested logit model (NMNL), which represents the probability of choosing an alternative over the nest alternative [46,48–52]. For all of the HEV and PHEV market forecasting studies reviewed here, these logit models are then input to a discrete choice model which is used to represent the response of individual customers [9,13–15,51,53–60].

The multinomial logit model (MNL) is based on utility theory wherein each individual will choose an alternative that maximize his/her personal utility (U) [16]. It assumes that the probability P that individual n will choose an alternative i from a set of alternatives j in C (where C is a set that includes all the potential alternatives) is given by:

$$P_{i,n}=P\left(U_{i,n}\geq U_{j,n},\ \forall j\in C_n,\ j\neq i\right) \tag{1}$$

The general multinomial logit model is defined as

$$P_{i,n}=\frac{e^{U_{i,n}}}{\sum\limits_{j\in C_n}e^{U_{j,n}}} \tag{2}$$

where

$$\sum_{i\in C_n}P_{i,n}=1 \tag{3}$$

$P_{i,n}$ is the probability that an individual n chooses an alternative i where $U_{i,n}$ is the utility function of an individual n chooses an alternative i [16]. The utility function equation is:

$$U_i=\sum_n\beta_nX_{i,n}+\varepsilon_i$$
$$\varepsilon_i\sim G(0,\mu) \tag{4}$$

$X_{i,n}$ is an explanatory variable (measurable or observable) for alternative i (i.e. incremental cost or fuel economy). β_n is the slope parameter for the explanatory variable $X_{i,n.}$ and ε_i is the alternative i random component [16]. The slope parameter β_n is calculated by knowing the elasticity $E^{P_i}_{X_{i,n}}$ of the probability (P_i) of an individual n choosing an alternative i with respect to a change in $X_{i,n}$. For example the direct elasticity $E^{P_i}_{X_{i,n}}$ formula can be modified to calculate the slope parameter $\beta_{n:}$

$$\beta_n=\frac{E^{P_i}_{X_{i,n}}}{(1-P_i)X_{i,n}} \tag{5}$$

Each alternative's elasticity can be estimated, or derived from survey data. The slope is then used to calculate the utility function for each alternative for each individual. The final step is to use the MNL function to estimate individuals' probabilities of choosing an alternative i. The method is applied for each group of individuals and each group of alternatives over the forecasting period by changing the utility function parameters for each alternative as a function of time or exogenous input.

In the discrete choice model, individuals are assumed to choose a vehicle that achieves the highest score or utility value [56]. The mathematical nomenclature of the discrete choice model presented here follows that of the study by Greene et al. [56]. The utility function equation is:

$$u_{i,j}=b\left(A_i+\sum_{l=1}^{K}w_lx_{i,l}+\varepsilon_{i,j}\right) \tag{6}$$

The utility function is defined as the weighted sum of the relevant vehicle attributes considered such as fuel economy, price, range performance and safety [56]. Because there will also be unquantified attributes for each individual, a random component is added to the utility function. So $u_{i,j}$ is the ranking score for *ith* vehicle for the *jth* individual, w_l is the weight of the *lth* attribute, $x_{i,j}$ and $\varepsilon_{i,j}$ is *jth* individual's random component for the *ith* make and model. A_i, is a constant that represent the value, in dollars, of the unmeasured attributes of vehicle i and b is the price coefficient [56].

The probability of an individual n will choose alternative i from k alternatives is the exponential of the utility of the alternative divided by the sum of all of the exponential utilities [56]. The probability that an individual will choose the *ith* make and model from the *kth* vehicle class is

$$p_{i|k}=\frac{\exp(bu_i)}{\sum_{l=1}^{L}\exp(bu_l)} \tag{7}$$

The NMNL has been used in the context of vehicle choice modeling to estimate the probability of a consumer choosing a vehicle class and then choosing among vehicle make and model as a nested decision [56]. The utility function for each class is modeled as the probability weighted average of the utility scores of vehicles within the class. For each class k the expected utility $U_k$is:

$$U_k=\frac{1}{b}\ln\left(\sum_{i=1}^{n_k}\exp\left(u_{l,k}\right)\right) \tag{8}$$

The probability that a consumer will choose a vehicle from class k is:

$$p_k = \frac{\exp(A_k + BU_{k,i})}{\sum_{K=1}^{n} \exp(A_K + BU_{K,i})} \tag{9}$$

where K is the summation of all vehicle classes and n is the number of vehicle classes. A_k is a constant that represent the value, in dollars, of the unmeasured attributes of vehicle class k. B is a slope parameter that measures the sensitivity of vehicle classes choices to the change in their expected value [56]. The probability of the consumer choosing vehicle i from class k is the product of Eqs. (7) and (9):

$$p_{ik} = p_{i|k}{}^* p_k$$

2.3.2. Review of key consumer choice based P/H/EV modeling studies

In this section we review some key studies that have used consumer choice modeling to estimate the adoption rate of HEVs, PHEVs and EVs.

The Advanced Vehicle Introduction Decision (AVID) [39] model was developed by Argonne National Laboratory (ANL) to predict consumer's vehicle purchase decision. The model was developed using multinomial logit model to predict consumer's preferences using weighted score for individual vehicle technologies and vehicle share. In this model, consumers are divided into early adopter (15%) and majority buyer (85%) groupings [39]. The study considered four multinomial logit models based on the four permutations of these consumer groupings and vehicle production being either constrained or unconstrained. Some of the scenarios considered included changes in consumer market preference, vehicle attributes, fuel prices, and technology production decisions [39]. There were 13 vehicle attributes in the model including vehicle price, fuel cost, range, battery replacement cost, acceleration, home refueling, maintenance cost, luggage space, fuel availability and top speed. The base case scenario used a gasoline price of \$1.50 gal^{-1} and a 7% HEV incremental price increase relative to the CV. Under these base case assumptions, the estimated HEV share under the unconstrained vehicle production decision was estimated to be $\sim$17% in 2020, $\sim$23% in 2035–2050. Vehicle adoption rate was found to be sensitive to gasoline price and HEV technology incremental cost. In the case of a gasoline price increase from \$1.50 gal^{-1} to \$3.00 gal^{-1}, HEV sales share increased to 56% in 2020 and to 64% from 2030 to 2050 [39]. In the case of an 18% increase in HEV incremental cost and gasoline price at \$3.00 gal^{-1}, HEV sales share is estimated to be between 5% and 8% from 2020 to 2050 [39].

The PHEV Market Introduction Study by Sikes et al. [4] developed a model of consumer choice to study the diffusion of new technologies in the US automotive market under different market and policy conditions. The Market Adoption of Advanced Automotive Technology model (MA3T) is based on nested multinomial logit (NMNL) model. MA3T projects HEV demand and its impact on energy demand and the environment. The model estimates the penetration rates of 26 vehicle technologies including HEVs and PHEVs for the passenger car fleet and light truck fleet over the period from 2005 to 2050. The model has four decision makers: consumers, government, fuel producers and vehicle produces/dealers. Three consumer types were considered: early adopters, early majority and late majority. The US was divided into nine divisions and each division into urban, suburban and rural statistical areas. Some of the factors included in the model were attributes such as retail price, performance, fuel economy, capacity, battery cost, vehicle range and fuel price. Other factors considered in the model are home refueling value, refueling infrastructure availability, subsidies, tax credits, housing type, consumers' attitude, driving behavior, technology cost reduction, vehicle and components supply constraint and vehicle makes and model availability and variations. Two scenarios that were considered are the base case and the PHEV success case [4]. Each scenario was examined in terms of different geographical regions, driver types, technology attitudes, recharge availability and vehicle technologies. HEV sales were estimated to range from 13 to 17 million in 2020 and PHEV sales to range from 332,975 current policy case to 3,569,400 in 2020 over different cases considered [4].

Diamond [13] developed a model of consumer demand using a consumer utility function dependent on the state-by-state market share of HEVs. The goal of this study was to examine the effects of tax incentives and gasoline price on HEVs sales in the U.S so as to communicate their effectiveness to policy makers. The primary model developed for this study was a cross-sectional model of hybrid vehicle market share derived from a behavioral utility function for automobile demand [13]. In this model Diamond accounts for consumer's income, average vehicle mileage and car dealership availability. The author observed that when supply is constrained, the sales will be determined by automakers internal distribution policies and there is a strong relationship between gasoline prices and hybrid adoption. He concluded that incentives will be effective only if they are provided upfront [13].

Social influences have been shown to play a role in determining consumer's openness to adoption of new vehicles and technologies, and consumer choice modeling has been used to model these effects. Axsen and Kurani [58] explored the role of social influences on the adoption of plug-in hybrid electric vehicles. The author used a discrete rational choice framework that models an individual's personal utility for a particular vehicle to choose among different alternative vehicle technologies [58]. In the work of Struben [14,15] and Sterman and Sturben [9], the adoption rate of alternative fuel vehicles was estimated by integrating diffusion models with discrete consumer choice theory. In this model, the consumer's preference to a specific vehicle platform was defined through the multinomial logit choice framework as the expected utility of the vehicle, including the dynamics of social influences, infrastructure, supply and vehicle demand [9,14,15]. Work by Bandivadekar [59] uses a discrete choice modeling approach to estimate the market penetration rates of new vehicle technology sales. The model was an extended version of the Heywood et al. [61] model and it included consideration of light-duty vehicle fleet sales, market share, age, scrappage rate, travel, fuel consumption and greenhouse gas emissions. Four different scenarios were considered and it was estimated that in 2035 the HEV sales will range from 15% to 40% and PHEV sales will range from 0% to 15% [59]. Greene et al. [56] developed a nested multinomial logit model to estimate diesel and hybrid vehicles rate would be 7–10% by 2008 and 15–20% by 2012.

Some studies have used the consumer choice model to predict the penetration rate of new technology vehicles outside the US, Bolduc et al. [57] have used a hybrid choice modeling framework to estimate the adoption rate of HEVs in Canada. The model was based on a multinomial logit model with consumer's utility function and contains latent psychometric variables [57]. Mau [53] developed a discrete choice model that uses a Canadian survey results to estimate HEV adoption rate in Canada. Feeney [55] has developed a vehicle choice model to predict the penetration rate of HEVs over 5–10 years, PHEVs over 5–20 years and EVs over 20 or more years in the NSW metropolitan region of Australia. Three different charging infrastructure availability scenarios were considered to measure the adoption rate of the vehicles [55]. Lee et al. [62] analyzed the effects of vehicle technology costs, infrastructure availability, and market share on the diffusion of HEV, EV, and HFCV in Korea using discrete choice models. The study found that reductions in technology cost and the

development of infrastructure increases the market share of these vehicles [62].

2.3.3. Consumer choice modeling summary

Consumer choice methods have been used in many vehicle adoption studies to model consumers' vehicle purchase and holding decisions. The models work by estimating the market penetration rate of new vehicle technologies using derived relationships between consumers' preferences and the attributes of a set of vehicles.

The advantages of consumer choice modeling come when it can use a rich historical dataset of consumer preference to model future consumer preference. The consumer choice models present in literature are more tractable, more transparent, and less complex than ABM models because of their ability to model the decision making of consumers as groups rather than as individuals.

The disadvantages of consumer choice modeling in this application are that historical sales data sets do not exist for purchasers of many P/H/EVs. For these developing technologies and markets, the sensitivities of consumers' purchasing decisions to the attributes of P/H/EVs must be indirectly derived from hypothesis, survey data, or other fields of consumer preference research.

2.4. Diffusion rate and time series models

2.4.1. Diffusion rate and time series modeling overview

Diffusion is defined as the process of acceptance of a new invention or product by the market. The speed with which a new product spreads through the market is called the rate of diffusion. The sales of new products in the market are influenced by internal and external factors which may be controllable or not [63]. There are many parameters that influence the rate of diffusion including metrics of innovation, communication, time, and the surrounding social system [64]. Diffusion rate and time series models seek to capture the life cycle of new products over time. Classical theories on diffusion include the concepts of classification of adopters, the role of social influence in adoption, and the S-shaped curve associated with the rate of an innovation's adoption. The diffusion of innovation is often modeled as a normal distribution over time. This distribution is divided into categories such as innovators, early adopters, early majority, late majority and laggards [64]. Innovators are the first adopters who are willing to take risks by purchasing new and innovative products. Early adopters are individuals who adopt an innovation following innovators. Early adopters are influenced by their social connections to innovators and other adopters. The rest of the categories will have slower adoption rate due to their lower level of social influence and lower financial status. Some of the best-known diffusion models in the marketing field are those of Fourt and Woodback [65], Mansfield [63], and Bass [66–68]. Time series and diffusion rate models have been applied to the prediction of diffusion in a variety of different markets including telecommunication, electronics, energy and transportation. The most widely used models are the Bass, Gompertz and Logistic models. These models have been used extensively to model innovation diffusion in automotive markets [34,45,49,66–85].

The Bass model is used for forecasting the adoption rate of a new technology under the assumption that no competing alternative technology will exists in the marketplace [67]. Bass divided consumers into two groups: innovators and imitators. Innovators are defined as adopters due to a mass-media effect, whereas imitators are defined as adopters due to a word-of-mouth effect. According to Bass there are two conditions at which the Bass model is appropriate for use in forecasting the long-term sales pattern of the new technology [67].

(1) The new technology has been introduced to the market for which the time period sales are observed.
(2) The new technology has not been introduced yet but it could have a market behavior similar to some existing technology with known adoption parameters.

In modeling the automotive market, the Bass model has been used to predict the adoption time and rate of new vehicles. For vehicles where sales data already exists, the parameters of the Bass model can be regressed. For vehicles where there is no historical sales data, analogs or surveys must be used to determine consumer's product adoption characteristics. These assumptions cause a higher degree of uncertainty and require more extensive model calibration and/or the inclusion of more variables such as price and advertising affects.

The Bass model formulation presented here includes the capability to perform both methods of model construction and follows the notation of [67]. The fraction of the available market that will adopt a product at time t can be defined as,

$$f(t)/[1-F(t)] = p + q^{*}F(t) \tag{10}$$

where the adoption at time t takes the form,

$$a(t) = M^{*}p + (q-p)^{*}A(t) - (q/M)^{*}[A(t)]^{2} \tag{11}$$

M: market potential, (total number of customers in the adopting target segment);
p: coefficient of innovation, (external influence);
q: coefficient of imitation, (internal influence);
$f(t)$: the portion of M that adopts at time t;
$F(t)$: the portion of M that have adopted by time t;
$a(t)$: adoption at time t;
$A(t)$: cumulative adoption at time t.

The equation of the generalized Bass model can be fit using existing sales data and the following equations:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}} \tag{12}$$

where

$$f(t) = \left\{ \begin{array}{ll} F(t), & t = 1 \\ F(t) - F(t-1), & t > 1 \end{array} \right\}$$
$$A(t) = M^{*}F(t),$$
$$a(t) = M^{*}f(t) \tag{13}$$

In addition, price and advertising affects can be incorporated into the Bass model through the inclusion of the function $x(t)$, where $x(t)$ can be a time dependent function of price or other variables.

$$f(t)/[1-F(t)] = [p + q^{*}F(t)]^{*}x(t) \tag{14}$$

A function $x(t)$ which includes consideration of price and advertizing can be calculated from

$$x(t) = 1 + \alpha^{*}\frac{[P(t) - P(t-1)]}{P(t-1)} + \beta^{*}Max\left\{0, \frac{[Ad(t) - Ad(t-1)]}{Ad(t-1)}\right\} \tag{15}$$

α: coefficient capturing the percentage increases in diffusion speed resulting from a 1% decrease in price;
$P(t)$: price in period t;
β: coefficient capturing the percentage increases in diffusion speed resulting from a 1% decrease in advertising;
$Ad(t)$: Advertising in period t.

Time series and diffusion models assume that products are redesigned, remodeled or updated and marketed in successive generations. Although the period between generations is different for different products and technology, each generation will follow the diffusion process. The ultimate diffusion rate for the product family will be the summation of the diffusion for each generation. In the diffusion modeling of automotive products, automotive product generations have been variously defined as a new generation of a current carline (Toyota Prius generation II) [86], as the introduction of a new technology within a current carline (Toyota Camry HEV) [86], or as an entirely new car line in the market (Chevrolet Volt) [86].

The Bass formula for the first seven generations of a product line is:

$$\begin{aligned}
G_{1,t} &= F(t_1)M_1[1-F(t_2)]\\
G_{2,t} &= F(t_2)[M_2+F(t_1)M_1][1-F(t_3)]\\
G_{3,t} &= F(t_3)\{M_3+F(t_2)[M_2+F(t_1)M_1]\}[1-F(t_4)]\\
G_{4,t} &= F(t_4)\{M_4+F(t_3)[M_3+F(t_2)[M_2+F(t_1)M_1]\}[1-F(t_5)]]\\
G_{5,t} &= F(t_5)\{M_5+F(t_4)[M_4+F(t_3)[M_3+F(t_2)[M_2+F(t_1)M_1]\}[1-F(t_6)]]\\
G_{6,t} &= F(t_6)\{M_6+F(t_5)[M_5+F(t_4)[M_4+F(t_3)[M_3+F(t_2)\\
&\quad [M_2+F(t_1)M_1]]]]\}[1-F(t_7)]\\
G_{7,t} &= F(t_7)\{M_7+F(t_6)[M_6+F(t_5)[M_5+F(t_4)[M_4+F(t_3)\\
&\quad [M_3+F(t_2)[M_2+F(t_1)M_1]]]]]\}
\end{aligned} \tag{16}$$

M_i: incremental market potential for generation i
t_i: time since introduction of *ith* generation and $F(t_i)$ is Bass Model cumulative function where p and q are the same for each generation

Estimating the market potential (M_i) is a critical part of the formulation of a diffusion model. The market potential need to be estimated for each technology as it represents the upper market bound for that technology. This has proven to be a complicating factor in automotive technology market diffusion modeling because of the need to understand the market potential for each vehicle class, the market preference for each technology within each vehicle class, and the share of manufacturers who will actually integrate a given technology into each vehicle class. The market potential must often change over the period of the analysis by integrating fleet expansion, vehicle class volume change, manufacturer performance and the availability of carline and technology. An example of a market potential for the passenger car HEV within the midsize class might be:

$$M_i = S^* P_{rf}{}^* S_h \tag{17}$$

M_i:market potential during year I;
S: total number of new US vehicle class sales;
P_{rf}: consumer's preference toward the technology vs. its incremental cost;
S_h: market share of the manufacturers selling HEVs or announced to have introduce HEV carline.

In addition to the Bass model, some HEV adoption studies have used the Gompertz and Logistic models to model HEV market diffusion. The Gompertz model is a time series mathematical model developed to describe human mortality age dynamics [87]. The Gompertz model equation is

$$f(t) = Me^{-bt}e^{-le^{-bt}} \tag{19}$$

where

$$\begin{aligned}
F(t_n) &= \sum_{i=1}^{n} f(t_i)\\
A(t) &= M^* F(t),\\
a(t) &= M^* f(t)
\end{aligned} \tag{20}$$

M: long-term market potential;
b: delay factor;
l: inflection point (time where 36.8% of the market potential is expected to be reached).

The logistic model used to model the diffusion of innovation is:

$$f(t) = \frac{M}{1+B^*\exp(-A^*t)} \tag{21}$$

where

M: long run market potential;
T: time index;
A: delay factor (between 0 and 1);
I: inflection point (time at 50% market potential to be reached);
$B = \exp(I^*A)$.

In general, the frameworks for using the Gompertz and Logistic models are similar to the framework of the Bass models in that all require the fitting of preexisting data, the concept of product generations, and a detailed estimation of market potential (M).

2.4.2. Review of key diffusion and time series P/H/EV modeling studies

In this section we review some key studies that have used diffusion and time series modeling to estimate the adoption rate of HEVs, PHEVs and EVs.

Lamberson [88] examined the adoption rate of HEVs using the Bass and Gompertz models. The study compared diffusion of HEV technologies to that of other automotive innovations and extrapolated results to the US fleet. Each model gave a different result though the Gompertz model was found to perform more favorably than Bass model [88]. He concluded that government incentives and regulation will play a major rule in HEV adoption. He uses a nonlinear least squares method to estimate the parameters of the Bass and Gompertz model based on historical, monthly US HEV sales. The total market penetration is estimated to be 1.6 million for the Bass model and 25.7 million for the Gompertz model [88]. The Bass model estimated that HEV sales will peak out on summer 2008 and then decline whereas the Gompertz model estimate it to increase until 2015 and then decline. It is estimated that on 2015 the annual HEV sales will be 2636 and 1,296,310 from Bass and Gompertz models, respectively [88]. In 2020 the HEV sales will be 33 and 1,208,039 from Bass and Gompertz models, respectively [88].

McManus and Senter [89] studied market models for predicting PHEV adoption. Two scenarios were considered, one without fixed saturation level and another with a fixed saturation level. In the fixed saturation scenario, Bass, Generalized Bass, Logistic and Gompertz models were used. The market potential was estimated to be around 1.8 million vehicles for the Bass, Generalized Bass and Logistic models. Market potential was estimated at 4.4 million for the Gompertz model [89]. PHEV sales were estimated to peak at 350,000 after 7 to 8 years from introduction [89]. In the scenario without fixed saturation levels, a model presented in Centrone et al. [90] and a consideration-purchase model were used.

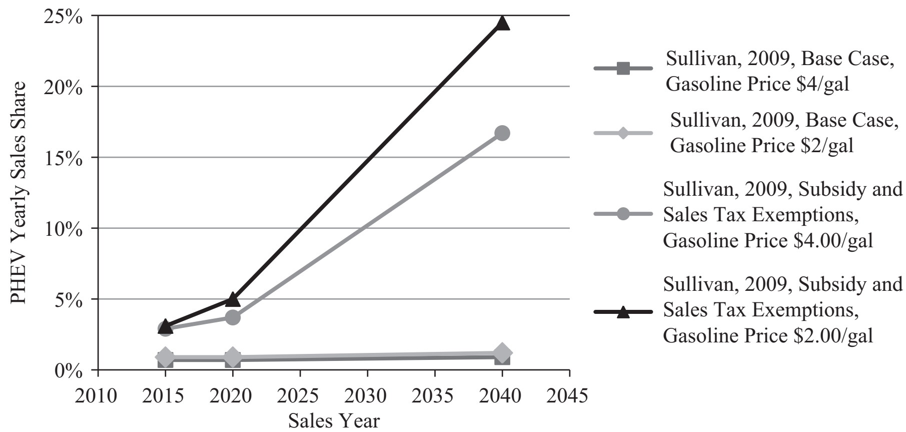

Fig. 1. PHEV sales penetration rate fleet share as estimated using agent-based method [2].

The consideration-purchase model accounts for vehicle sales, stock and scrappage. For PHEV incremental costs varying between $2500 and $10,000, the PHEV penetration rate is estimated to be 118,793 to 4726 units in 2015, and it is estimated to be 1,891,576 to 84,341 units in 2025, and it is estimated to be 6,021,141 to 379,615 units in 2035 [89].

Cao [91] used an extended Bass model with variable market potential to model HEV market diffusion. He included forecasted gasoline prices for the period 2003–2025 and a prediction of consumer's evolving awareness of HEV technology. Some of the assumptions considered are that the coefficients of the Bass model do not change over time, there exists no interaction among vehicle technologies, vehicle technology supply always equals or exceeds their demand and the diffusion rate is not effected by government policies or marketing strategies. The model was tested under different scenarios of: HEV awareness influence, gasoline price change, and market potential scenarios. In the scenario analysis, the market potential was assumed to be around 10% of the total US registered vehicles in 2000, and consumer awareness is assumed to increase by 2% per year. Under these conditions, results showed two peaks in diffusion rate due to first-time HEV purchases (2013) and replacement purchases (2023). HEV sales were estimated to reach 510,000 in 2008 and 2 million in 2013. In the two gasoline price scenarios considered, gasoline price is assumed to increase by 25 cents and 50 cents per gallon per year from 2007 on. The average annual HEV sales are estimated to be 2.2 million and 2.8 million from 2011 to 2025 for these two scenarios, respectively.

Jeon [86] examined the penetration rate of HEVs, PHEVs and EVs until 2030 based on the Bass diffusion model. This model used the concept of successive generations to overcome the limitations and market saturation problems of the Bass model. The generations were defined by either a start of new technology carline or a new generation of current carline technology. The market potential was estimated for each generation as the approximate average sales of the US vehicle fleet or class in which the technology exist multiplied by the generation period. His model estimated the annual US sales of HEVs, PHEVs and EVs to reach 5 million, 1 million and 2.1 million, respectively.

Becker [92] reports the rate of electric vehicle adoption using the Bass model under two gasoline price scenarios and accounting for vehicle purchase price and operating costs. In the baseline scenario the EV will have a penetration rate of 3% in 2015, 18% in 2020, 45% in 2025 and 64% in 2030 of the total US light vehicles sales [92]. Trappey and Wu [93] evaluated three forecasting methods on large and small data sets. An extended logistic model fit large and small datasets better than a simple logistic or Gompertz model and was well suited to predict market growth with limited historical data [93].

Other studies have used diffusion models to estimate the diffusion rate of HEV in countries other than the US. In a study by Won et al. [94] a Bass diffusion model was used to estimate the adoption rate of PHEV in Korea by using US HEV sales data. The study did not test or use any historical vehicle sales data in Korea but they only considered the total vehicles registered and the year vehicle sales. They limit their analysis to small sized HEV cars excluding light trucks and other larger vehicles [94]. In their estimation of Bass model parameters they assume that the market potential for HEVs are estimated from US HEV sales data [94]. By 2032 the adoption rate of PHEV was estimated to reach its maximum where in 2052 the Korean market would be saturated with PHEV [94]. Higgins et al. [95] have developed a diffusion model to predict the penetration rate of P/H/EVs across Victoria, Australia over the period 2011–2030. The model includes features of choice modeling and was calibrated using survey and focus groups [95]. Muraleedharakurup et al. [96] used Gompertz growth and Logistic models to forecast the adoption rate of HEV in the UK up to 2030. The Bass model was not used due to the absence of past vehicle sales data. The study considered technology life cycle net cost in the predicting of HEV adoption rates although they did not explain how they integrated the life cycle cost in the penetration rate curve fit [96]. The analysis was performed by specifying the market segment, estimating the market potential, estimating the economic cost and estimating the technology penetration rate. The study considered the UK fleet and results show that the penetration rate will achieve 7.5% by 2020 and 16% of the UK vehicle market by 2030 [96]. Some of the factors found to affect HEV penetration rate are the oil prices and increase in diesel vehicle penetration [96].

2.4.3. *Diffusion rate and time series modeling summary*

Diffusion and time series models are a means to describe the process of market acceptance of a product over time. They simulate consumers' adoption of a product using one of a variety of theories on general market diffusion, and they generally incorporate the concept of product generations, and an absolute market potential.

The advantages of these models are that they are easy to implement, and can be fit to the historical trend of the vehicle technology or similar technologies. The disadvantages are that the time of peak sales needs to be known in advance, these models are not valid to simulate the diffusion of a product where there

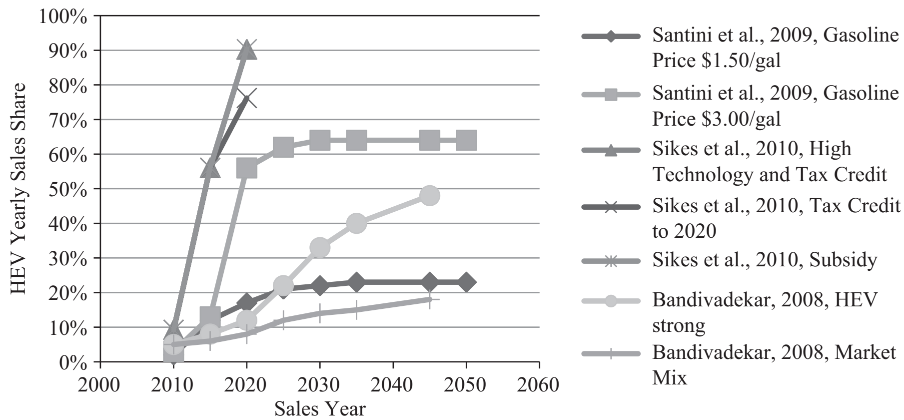

Fig. 2. HEV fleet penetration rate estimated using consumer choice method [4,39,59].

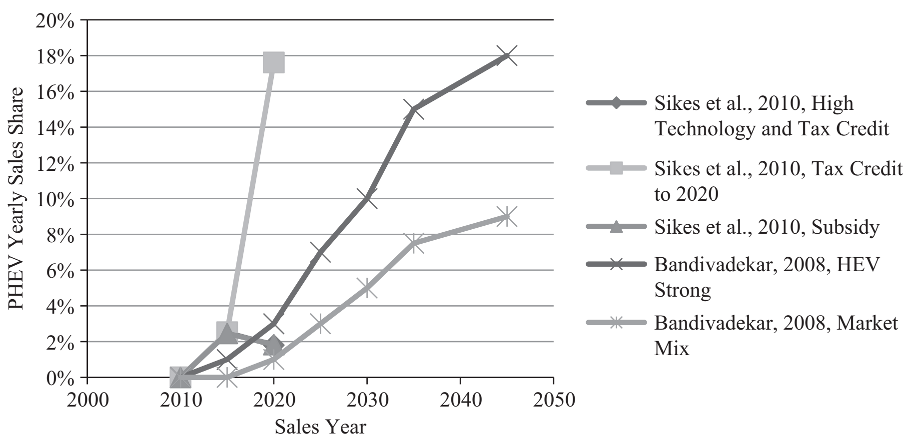

Fig. 3. PHEV fleet penetration rate estimated using consumer choice method [4,59].

exists a competing product, and the ultimate market potential for each vehicle must be estimated outside of the model.

2.5. Other models

Some studies have examined the penetration rate of HEVs using existing forecast, survey data, or supplier's capabilities. A study by Balducci [97] examines the market potential for PHEVs in the US. Three scenarios were examined for PHEV market penetrations from 2013 to 2045. The first scenario was based on existing forecast of hybrid technology and the estimated PHEV shares as derived from EPRI and NRDC estimates [97]. The second scenario was based on asking domain experts for the best judgment under a given set of PHEV conditions that range from marginal cost to tax incentives. The last scenario was based on estimates of the supply capabilities of automakers and battery manufacturers. The study found that in 2045, the PHEV market penetration is estimated to reach 11.9% using the first scenario, 30.0% using the second scenario and 73.0% using the third scenario [97]. A Monte Carlo simulation was used by Tran et al. [98] to test different conditions that might influence the adoption of CV, diesel, HEV, PHEV, BEV and FC technologies over the period 2000–2030 in the EU. A study by Eggers and Eggers [99] developed a choice-based conjoint adoption model to predict HEV, PHEV and EV penetration rates using consumers preference modeling. In another example, Curtin et al. [100] examined the purchasing probability of HEVs and PHEVs. The analysis was based on the results of interviewing a nationally representative sample of 2513 adults from July to November 2008 in US [100]. The data showed that social factors can change consumers purchasing decisions, but that economic incentives dominate consumers' automobile purchasing decisions [100].

3. P/H/EV market forecast modeling discussion

In this section, we present the results of each reviewed study where the authors performed a market penetration rate study for the US that used a model of the US vehicle fleet, and that attempted to predict HEV, PHEV or EV market share as a function of time. The results for each modeling type are presented together.

3.1. Agent-based models

Using agent-based models, only Sullivan et al. [2] estimated HEV, PHEV or EV market penetration according to the above requirements. Eppstein et al. [11] predicted the adoption rate of PHEVs as a function of time but without specifying initial start date. Sullivan et al. [2] estimated fleet penetration and new PHEV sales for 2015, 2020 and 2040 using two fuel price scenarios. The four cases considered in each fuel price scenario are, (1) a base case, (2) a case under which automobile manufacturers subsidize the incremental cost of PHEVs, (3) a case under which sales tax for PHEVs is exempted, and (4) a case under which both 2 and 3 are combined. The results presented in Fig. 1 show that subsidies and sales tax exemptions are required to stimulate large scale PHEV adoption. The increase of PHEV sales due to these policy

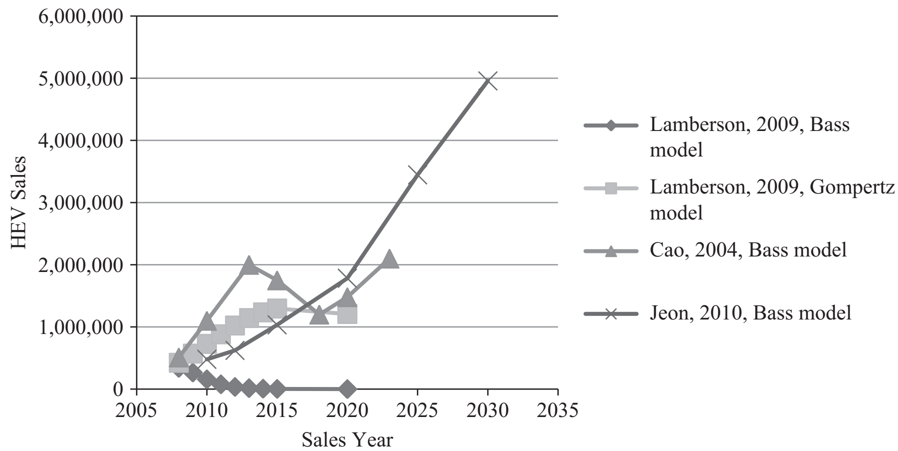

Fig. 4. HEV penetration rate estimated using Bass and Gompertz methods [86,88,91].

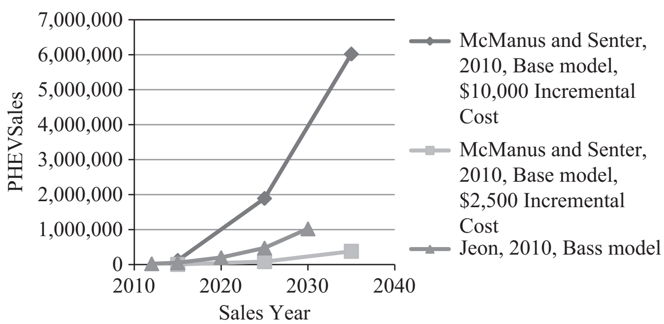

Fig. 5. PHEV penetration rate estimated using diffusion method [86,89].

interventions is estimated to be 4–5% in 2020 and 17–24% in 2040 over the base case. An increase in fueling costs to $4 per gallon increases PHEV adoption by 1% in 2020 and 8% in 2040 [2].

3.2. Consumer choice models

Using consumer choice models, a few studies have estimated HEV, PHEV or EV market penetration according to the above requirements. The HEV sales rate was most completely estimated by Sikes et al. [4], by Santini and Vyas [39], and by Bandivadekar [59]. A comparison of these results is shown in Fig. 2.

The differences between the results of these studies are due to the variation in modeling methods, model parameters, and assumptions as discussed in previous sections. The variation among studies in HEV penetration rate is 82% in 2020 and 46% in 2045. Santini and Vyas [39] estimate that the HEV adoption rate will increase by ~41% with an increase in fuel price of $1.5 per gallon. Sikes et al. [4] show higher HEV adoption rate where the variation among the scenarios are due to differing scenarios of HEV ownership cost. Overall, these studies show that HEV market penetration is increased under conditions of lower incremental cost or higher CV operation cost.

Fig. 3 shows the results of the Santini and Vyas [39] and Bandivadekar [59] models of PHEV penetration rates. The scenario at the Santini and Vyas of tax credit to 2020 show that the adoption rate will reach 18% by 2020 but this will be accomplished through PHEVs taking some of HEV market share. Under the model of Bandivadekar, the variation between scenarios results are relatively large, but under no scenario does PHEV technology fail to gain market share.

3.3. Diffusion rate and time series models

Again, only a few diffusion rate studies have been constructed that meet the comparability requirements presented above. Lamberson [88] used the Bass and Gompertz model to estimate HEV and PHEV new vehicle sales. He used the US monthly vehicle registration data. Cao used an extended Bass model with variable market potential where Jeon used the Bass model with successful generation. Results are presented in Fig. 4 [86,88,91].

The PHEV penetration rate was estimated by the studies whose results are presented in Fig. 5, McManus and Senter Jr. [89] for two PHEV incremental cost scenarios. The increase in PHEV sales due to the lowered incremental costs are estimated to be ~100,000 vehicles in 2015, 1.8 million on 2025 and 5.6 million on 2035 this was due to a decrease in PHEV cost by $7,500 [89]. The results from Jeon [86] show that PHEV sales will slowly increase to reach 1 million vehicles by 2030, primarily due to a very fast increase in HEV market share.

As shown in Fig. 6, the adoption rate of electric vehicles was estimated by Becker [92] using two energy price scenarios. The per year sales differences between these two electric vehicle adoption rate scenarios increases from 256,000 in 2020, to 480,000 in 2025, and decreases to 336,000 in 2035 [92]. Jeon [86] estimated that EVs will have a relatively high market share compared to PHEVs and that vehicle sales will increase to reach ~2 million per year by 2030.

Results presented show there is a large variation between models, studies, and within each study scenarios. In the next section, a set of recommendations provide some guidance in improving the validity and usefulness of P/H/EV market penetration models.

4. Recommendations and conclusions

This study has reviewed and analyzed the primary purposes, methods, and results of studies of P/H/EV market penetration. The purposes of performing vehicle technology market diffusion studies are to (1) understand whether P/H/EVs will be present in the US vehicle fleet, (2) understand the role of policy in encouraging P/H/EVs market diffusion, and (3) determine the future number of P/H/EVs for planning purposes. The primary methods used in literature are agent-based behavior models, consumer choice models and market diffusion models. Each method is analyzed to understand its strengths and weaknesses. The results of these studies have been shown to be highly variable due to differences within and among studies in terms of the

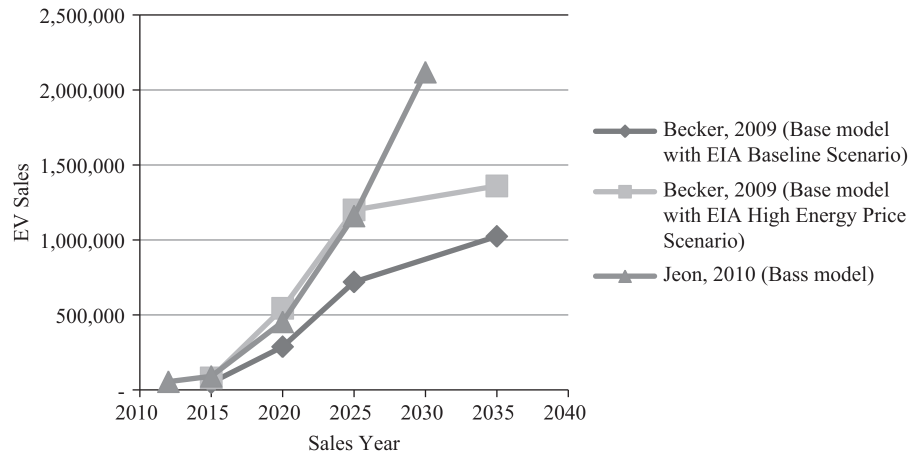

Fig. 6. EV penetration rate estimated using diffusion method [86,92].

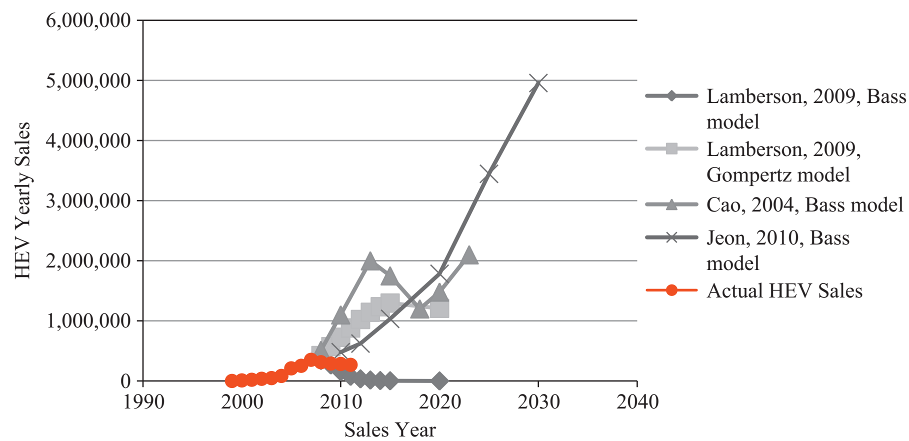

Fig. 7. Actual and estimated HEV penetration rate using diffusion rate method studies.

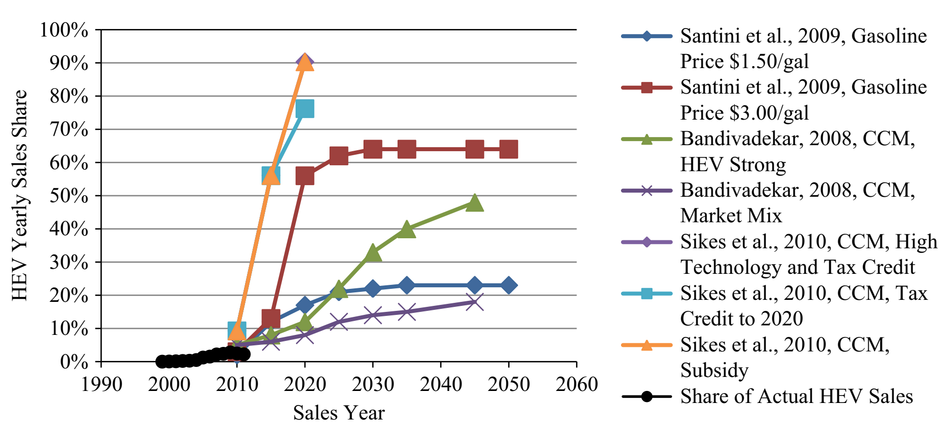

Fig. 8. Share of actual and estimated HEV penetration rate using consumer choice method studies.

methods used (agent-based methods, consumer choice methods, and diffusion rate models), the values of important parameters (including total available market), assumptions (including fuel costs), and uncertainty in policy and market condition scenarios.

On the basis of these findings, we can synthesize recommendations for improving the utility of these studies for decision making by society and in the vehicle and utility industries.

We recommend an improved interface between modeling and surveys: Most studies do use consumer survey data to inform their adoption rate modeling, but the fidelity with which the consumer is modeled does not match the richness of data that could be derived from survey. For instance, many adoption rate models divide consumers into categories of innovation including: innovators, early adopters, early majority, late majority and laggards as defined by Rogers [4,64,100]. First, it is unclear whether the innovation categorizations developed for low-operation cost consumer products are applicable to the high operations costs associated with vehicle fuel economy preference.

Second, none of the P/H/EV market preference surveys performed to date poll consumers on their openness to automotive innovation, so as to identify surveyed preferences with these categories.

We recommend the inclusion of modeling of vehicle supply and the actions of automakers: None of the reviewed studies have attempted to measure and model automakers actions and plans for P/H/EVs. Automakers represent the supplier of the technology under consideration and they are constrained by factors including budget, technology availability, brand preference, and preexisting product plans. The primary assumption for most of these studies is that manufacturers are able to meet the proposed demands for P/H/EVs. This assumption has not been strongly challenged, but numerous studies have shown that policy demands and consumer demands for fuel economy can be met in ways that do not require the mass-production and mass-marketing of P/H/EVs [8,10].

We recommend the inclusion of modeling of federal and state policy and its effect on automotive markets: The US automobile industry is highly regulated industry where some level of incentive for advanced automotive technologies is provided by regulatory compliance requirements. Historically, P/H/EVs, have been developed in response to federal actions including Corporate Average Fuel Economy (CAFE) regulations [11], clean air standards [101], and even research and development programs [102]. None of the studies reviewed here considered, for instance, CAFE compliance costs in projecting consumer acceptance of P/H/EVs despite a long history of studies describing the role of CAFE regulations in influencing automaker vehicle designs.

We recommend the inclusion of modeling of competition among technologies: Most of the models assumed that consumers will consider the discrete choice between the new purchase of a P/H/EV and a CV. Most of the studies reviewed here did not consider how consumers will understand competition among the other technologies that will be available. The majority of models assume that one technology (HEV, PHEV or EV) will dominate for the next 10–30 years and the market of these vehicles will not be lost to a new technology. Most models did not consider automakers' rate of adoption of improved and fuel efficient CV technologies [8,10]. Most models did not consider the presence of HEVs or other advanced technologies in the used car market.

We recommend improved modeling of market volume and vehicle classifications: A majority of the models reviewed here consider the vehicle fleet to be monolithic; only a few of the studies consider the effect of variation in consumer preference for HEV, PHEV and EV technologies among vehicle classes and types. For the market diffusion and time series models, the market share of vehicle fleets, classes and makes must be estimated and integrated into the modeling in advance to set the correct market potential for every vehicle technology. Therefore studies that use market diffusion and time series models cannot be used to predict the market potential, instead they can only be used to describe the trajectory between the present and a predefined future market equilibrium point.

We recommend improved sensitivity analysis that can support and verify the model results and provide a guideline to future improvement in the model, parameters and assumptions: Some of the studies reviewed here have performed scenario analyses and comparison to historical HEV sales data to support the validation of the model.[1] But in general, the studies reviewed here did not perform sensitivity analysis to understand the robustness of the model itself. Every model reviewed uses regressive relationships to fit modeling parameters such as elasticities and utility functions, but the uncertainties associated with these fitted parameters are not included in the modeling results and discussion. In general, the authors have found that many of the conclusions of market modeling studies are quite sensitive to uncertainties in modeling parameters and that this uncertainty should be expressed transparently. These considerations will improve the means for measuring the validity and accuracy of the model and study conclusions.

This literature review describes the current state of the art in P/H/EVs market penetration rate modeling. P/H/EV technologies have come to market due to their reduced petroleum consumption and consequent value to consumers, society, automakers, and policymakers. In general, these studies are found to be relevant and defensible within their scope, but the inclusion of these results into larger studies will be problematic. The large and unquantified sources of uncertainty and the large variability among studies makes synthesis of the results of P/H/EV market penetration studies more difficult. By following the recommendations of this literature review, it is hoped that the field can expand its impact and relevance to decision making entities in the government, utility and automakers.

[1] Although none of the studies reviewed here would assert that their findings have predictive power, Figs. 7 and 8 in the appendices presents the same results as compared to the actual HEV sales data. These comparisons are included in this review to support the recommendations and are not included to critique the performance of the market modeling performed in these studies.

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